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Visually Lossless Compression of Retina Images

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***Abstract*—Digital images of a rather high resolution are widely used in modern medical practice. Due to their large size, there exists necessity to compress them before storage or transmission via communication lines in telemedicine. Possibilities of lossless compression are limited and one often has to apply lossy compression with providing acceptable diagnostic quality of compressed data (with ensuring visually lossless compression). This paper proposes ways to carry out such a compression in one iteration, i.e. quickly enough with application to retina images. An efficient coder based on discrete cosine transform (DCT) in 32x32 pixels blocks is analyzed. It is shown that mean squared error (MSE, or PSNR (peak signal to noise ratio) of introduced distortions can be predicted by estimating distribution of alternating current (AC) DCT coefficients in a limited number of 8x8 pixel blocks and very fast processing of these DCT coefficients. We present approximating (predicting) curves obtained by regression of several types of simple functions into scatter-plots. This allows setting coder parameter (quantization step - QS) to provide a desired MSE. Applicability of the proposed way of prediction approach is demonstrated experimentally for real-life retina images.**

Keywords—lossy compression; noise; image; metric prediction

I. Introduction

Medical imaging has become one of the main tools in everyday medical practice [1]. A lot of images are acquired, stored and transferred via telecommunication channels in telededicine systems. Meanwhile, image size is quite large and it often exceeds 1 MB [2]. This can arise problems in image storing (because of limited space in computer memory) and, especially, in data transmission. Thus, image compression is needed [2-4].

It is known that lossless and lossy compression can be used. The former approach presumes that no losses (distortions) are introduced and, thus, all valuable information is preserved. Unfortunately, compression ratio (CR) in this case is usually small (for such standard formats as TIFF, GIF, PNG, etc.) and it can be not acceptable. This stimulated intensive research in lossy compression of medical with application to different types of medical images. The general tendencies are the following. First, numerous experiments with specialists have been carried out to determine what CR or what other parameters are acceptable in the sense that diagnostically valuable information is not lost or destroyed [2, 5, 6]. Second, it has been shown that recommended CR or other parameters depend upon several factors: medical image type, is a used image grayscale or color, what object is imaged, etc. [3]. Third, most considered methods of lossy compression are based either on wavelets or discrete cosine transform (DCT) as JPEG or more advanced schemes [2, 4, 7]. For better coders, a recommended CR is larger [2] although a CR to be used also depends upon image complexity.

Retina images are widely used nowadays [2, 8, 9]. They have several peculiarities. First of all, these images are color where less information is contained in blue component compared to red and green. Second, the standard image size is quite large (see images in the specilized database DRIVE for diabetic retinopathy [10]). Third, lossy compression can be rather effectively applied to this type of images – the recommended values of CR are always larger than 10 and, according to [2] can reach 50 for efficient coders. However, opinions of specialists concerning quality of compressed images can differ in this case.

To our opinion, CR to be provided should depend on image content (complexity) and quality. Recently, we have carried out many experiments on how to provide invisibility of distortions introduced by lossy compression techniques [11-13]. It has been shown that there are certain threshold values of image quality metrics when introduced distortions are still invisible (cannot be noticed with high probability) [13]. It has been also demonstrated that compression with providing a desired value of quality metric can be done either iteratively with multiple compression/decompression (more accurately) [11] or using certain recommendations on coder parameter, e.g. quantization step [11, 12], less accurately.

The obtained results were quite general although they have not been verified for medical and/or color images. The DCT based coder AGU [14] was mainly tested. Besides, multiple compression/decompression requires time about a few seconds and it is often needed to carry out lossy compression with a desired quality faster.

To get around these shortcomings, a new approach has been proposed recently [15, 16]. Its essence consists in the following. Mean square error of distortions introduced by lossy compression is predicted from analysis of a comparatively small number (e.g., 3000) of alternating current (AC) DCT coefficients determined in 8x8 pixel blocks. This prediction has been shown accurate - errors of MSE (mean square errior) prediction were less than 1 dB. This allows to set quantization step (QS) for DCT-based coders without multiple compression/decompression to provide a desired MSE (or MSE satisfying certain requirements) very quickly and then to apply compression.

Testing has been done for standard optical grayscale images and components of multichannel remote sensing images. Our goal here is to consider applicability of the designed approach to color medical (retina) images. Note that the use of non-standard coder has both advantages and drawbacks. One advantage is that it is possible to reach larger CR [14].

II. DCT-Based Compression and Compression and Parameters Prediction

Modern lossy compression techniques (JPEG, JPEG2000, SPIHT, AGU, ADCT) mainly employ orthogonal transforms [3, 11, 17, 18] due to their ability to represent data in a sparse form. DCT and wavelets are the most popular and they are put into basis of most standards of signal/image/video lossy compression.

Methods based on DCT have several advantages. First, they are able to perform, at least, not worse than wavelet based standard JPEG2000 [11]. In particular, this relates [11, 18] to the DCT-based compression technique AGU [14] that we consider below [11]. It performs two-dimensional (2D) DCT in 32x32 pixel blocks, exploits bit-plane coding of quantized DCT coefficients and uses embedded deblocking of decompressed images. The use of 32x32 pixel blocks provides better decorrelation of data than in 8x8 pixel blocks. Bit-plane coding in the considered application performs better than arithmetic coding. Recall that CR for AGU is controlled by QS where a larger QS corresponds to a larger CR for any image.

At the very beginning, we have decided to analyze a simpler case of applying AGU separately to R, G, and B components of retina images. We have taken three retina images of slightly different complexity (with different amount of details important for diagnostics}. MSE of introduced losses as functions of QS for three color components of three tested images are presented in Fig. 1. Properties of the considered test images slightly differ due to variation of imaging conditions.

Analysis of these dependences shows the following. The dependences are slightly different for different color components and different color images. More careful analysis has shown that MSE grows faster for more complex structure (containing more details) images. The dependences also differ for color components where the largest distortions are usually observed for blue component. Note that similar conclusions can be drawn from Fig. 4 in [2] where JPEG and wavelet based coders were studied.

Let us rely on opinions of specialists presented in [2]. They state that CR can be up to 30 for JPEG and up to 50 for wavelet based coder. This allows determining that MSE of introduced losses can be about 6 for red and green components and up to 10 for “less important” blue component. According to data in Fig. 1, this takes place for QS about 30 for red component, for QS about 30 for green component and about 20 for blue component of one test image. Then let us see what CR can be provided in these cases.

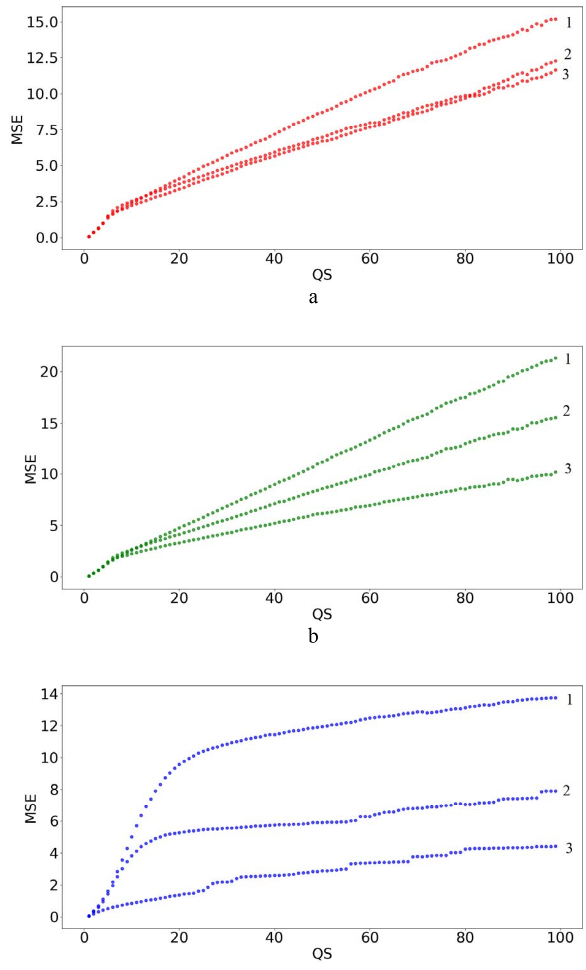
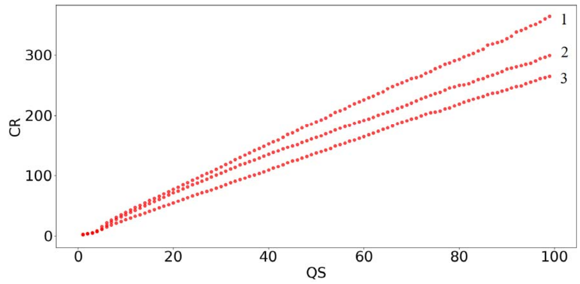


Fig. 1. Dependences of MSE on QS for three different test images (1, 2, 3) for R (a), G (b) and B (c) color components

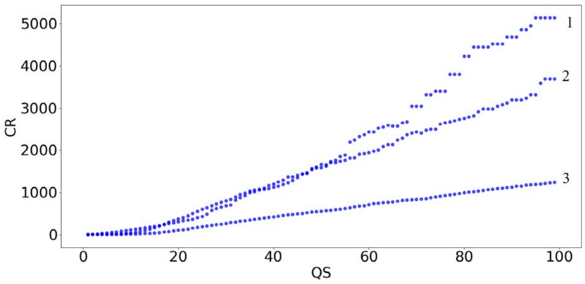
Fig. 2 represents dependences of CR on QS for red and blue components (the results for green component are intermediate). It is seen that red component for QS about 30 is compressed with CR larger than 80 (green component for QS about 30 is compressed with CR about 90). The problem is with blue component image that is compressed worse and the reason is that this component image is quite noisy (Fig. 3 presents original, compressed and difference images for blue component).

As it is seen, noise is partly removed by lossy compression. This effect has been earlier described in several papers (see, e.g. [18] and references therein).

Thus, our first task is to provide a desired MSE in compressing component images separately. It has been noticed in [15, 16] that MSE is approximately equal to QS2/12 for small QS. It has been also noticed in [19] that compression parameters (in particular, CR) strongly depend upon percentage of zeros for quantized DCT coefficients P0. Thus, let us check a hypothesis that we can represent MSE as $MSE = (QS^2/12) f(P_0)$ where $f(P_0)$ is some function supposed to be known in advance.



a



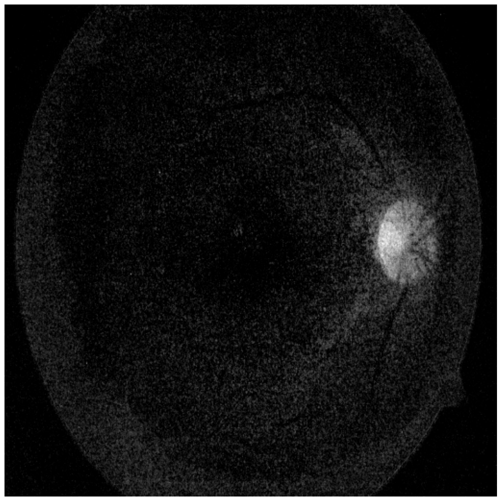
b

Fig. 2. Dependences of CR on QS for three different test images (1, 2, 3) for R (a) and B (b) color components

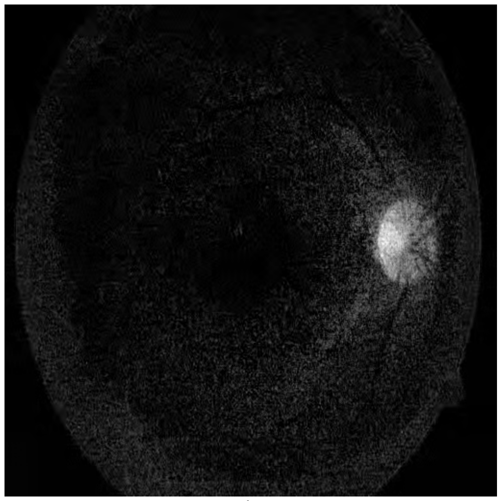
To obtain $f(P_0)$, we have used 10 test images compressed component-wise by AGU with different values of QS. MSE values have been calculated for each case and then normalized by the corresponding $(QS^2/12)$. Besides, P_0 values have been determined for 8x8 pixel blocks. Note that P_0 is calculated very easily as $N_0/63N_{bl}$ where N_0 is the total number of AC DCT coefficients with absolute values smaller than QS/2 and N_{bl} is the number of image blocks of size 8x8 pixels for which DCT coefficient have been calculated by 2D DCT.

As the result, the scatter-plot of $12MSE/QS^2$ vs N_0 has been obtained. This scatter-plot is presented in Fig. 4 (points that relate to red, green, and blue components are shown by the corresponding colors). First, it is seen that we have a strict dependence that can be determined by regression (see the next Section). Second, MSE is about $(QS^2/12)$ for P0 smaller than 0.6 but $12MSE/QS^2$ can be considerably smaller than unity for larger P0

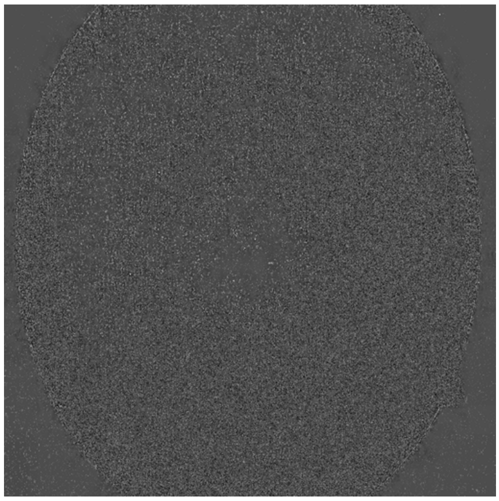
Having such a dependence at disposal, it is easy to obtain a set of AC DCT coefficients, to determine P_0 for a given starting QS (e.g, 20) and then to calculate QS needed to provide a desired MSE ($QS=(12MSE/f(P_0(QS)))^{1/2}$). Next Section briefly analyzes regression variants.



a



b



c

Fig. 3. Original (a), compressed with QS=40 (b) and difference (c) images

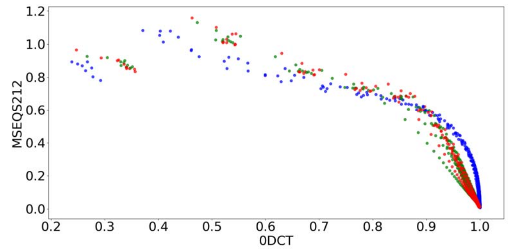
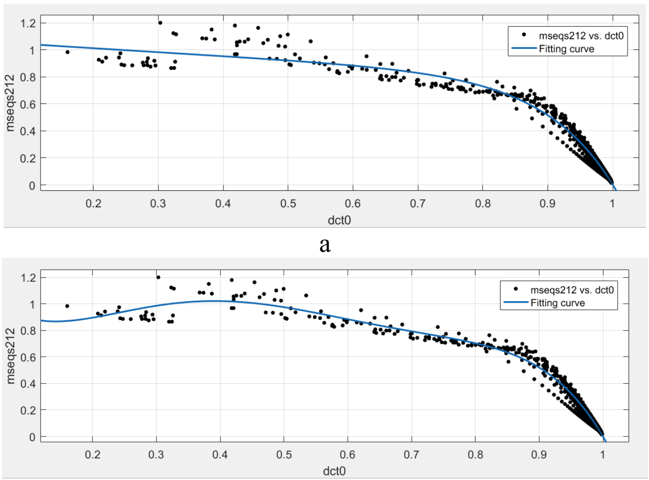


Fig. 4. Scatter-plot of normalized MSE vs P_0 for component-wise compression

III. Regression Variants

Regresiion by curve fitting into scatter-plots has practically become a trivial task nowadays. There exist standard tools for fitting in Excel and Matlab, there are also standard quantitative criteria that characterize accuracy (quality) of fitting [20]. In particular, fitting is considered good if goodness-of-fit values R2 approach unity (exceed 0.9 at least) and root mean square eror (RMSE) is small enough.

A user of aforementioned tools that controls and analyzes fitting results has to decide what kind of functions to use, what are restrictions on function values and its behavior. Analysis of data in Fig. 4 shows that fitting function should be rather smooth, it should be either monotonous or have maximum for P_0 about 0.4 and the function values have to be positive for all range of possible values of P_0.



a

b

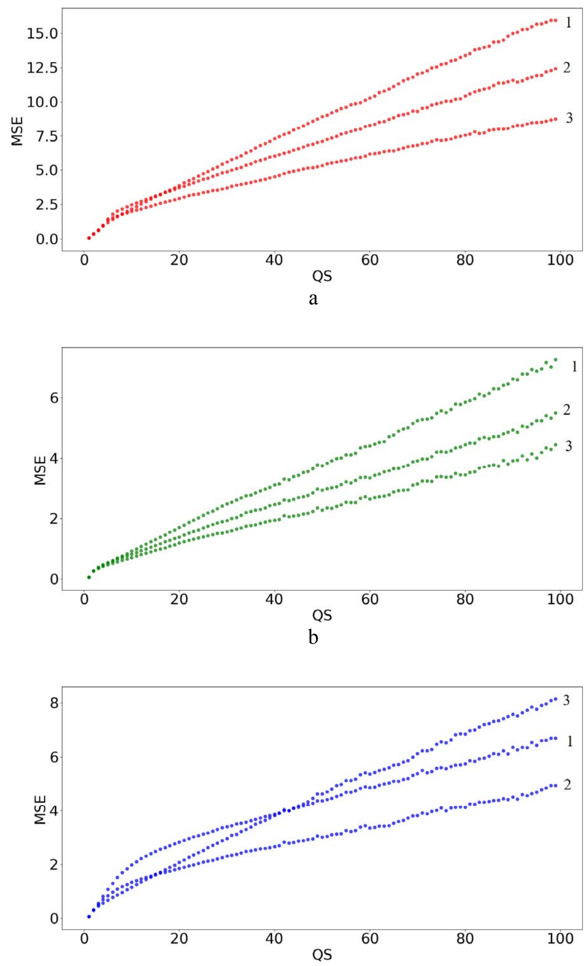
Fig. 5. Scatter-plots and approximating curves for the sum of two exponentials (a) and the fifth order polynomial (b)

Keeping this in mind, we have analyzed several types of functions for curve fitting into the scatter-plot in Fig. 5,a. These functions are the sum of two exxponentials with four adjustible parameters (R^2 =0.982, RMSE=0.030, just this fitting function is presented in Fig. 4), Fourier series fitting (R^2=0.956, RMSE=0.047), fifth order polynomial (R^2=0.985, RMSE=0.027, Fig. 5,b), and power function (R^2=0.980, RMSE=0.032). To our opinion, the sum of two exponential functions ($f(P_0)$=-6.125e-05*exp(9.477*x) + 1.073*exp(-0.2914*x)) and the fifth order polynomial are equally good good choices.

IV. Other Color System and Compression Results

Recall that we had problems with B component image for RGB representation of data and component-wise compression. Recall also that JPEG applied to color images converts them first to other color system. So, let us convert original image to YCrCb color system (assumed to be one of the best) and consider compression of each component.

The compression results (the dependences of MSE on QS and CR on QS) are represented in Figures 6 and 7, respectively. As it is seen, the results for all three components have become closer. This is because noise present in blue component image has been spread between all three components after conversion. Moreover, noise has become practically invisible. This is seen well in Fig. 8 where all three component images are presented. Besides, it is seen that all three components contain valuable information that has to be preserved by lossy compression.



a

b

c

Fig. 6. Dependences of MSE on QS for three different test images (1, 2, 3) for Y (a), Cr (b) and Cb (c) components

Analysis of data in Fig. 6 shows that the desired MSE can be provided for QS about 15…20. In this case, CR values for component images are from 20 to 70 (see data in Fig. 7), i.e. at the same level as in [2]. Fig. 9 presents original color image and the compressed image where QS=15 was used for all three components. The provided CR is equal to 114 that is practically the same as recommended in [2] for wavelet coders. Introduced distortions are practically invisible. Similar values of CR varying from 90 to 120 were observed for other studied retina images. Average time for retina image compression using CPU Intel(c) Core (c) i7-4710 HQ 2.5 GHz takes less than 2 seconds. Decompression takes approximately the same time.

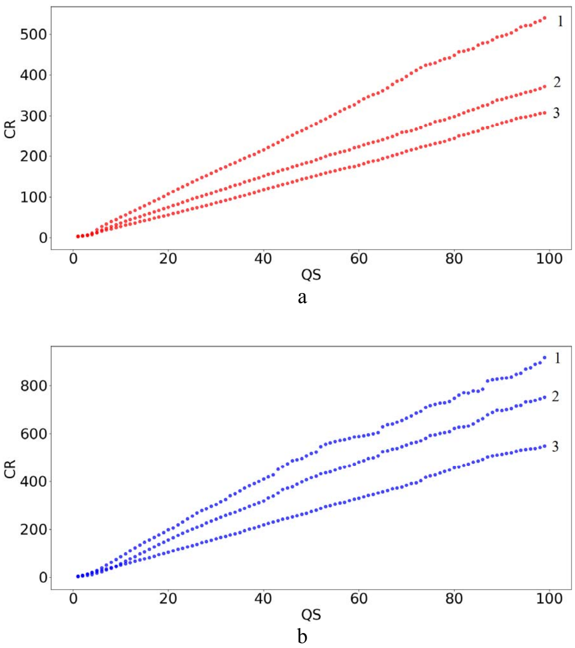


Fig. 7. Dependences of CR on QS for three different test images (1, 2, 3) for Y (a) and Cb (b) components

We have also obtained the joint scatter-plot of $12MSE/QS^2$ vs N_0 for compressing Y, Cr and Cb components by AGU. The scatter-plot is presented in Fig. 10. Not surprisingly this scatter-plot is very similar to that one presented in Fig. 4. Moreover, aforementioned exponential and polynomial approximations fit this scatter-plot with R^2 about 0.976 and RMSE about 0.040. Thus, the same procedure for QS determination is valid.

V. Conclusions

In this paper, we have considered peculiarities of retina image lossy compression with desire to simultaneously provide a rather large CR and practically invisible distortions introduced. It is shown that it is possible to provide a desired MSE of introduced losses without iterative compression and decompression of images due to the proposed procedure of MSE prediction. This procedure uses percentage of zero-valued DCT coefficients after quantization for a given QS to determine a needed QS and to perform compression using it. The prediction is fast since it exploits 2D DCT in a limited number of 8x8 pixel blocks.

The approach can be further advanced and generalized for 3D version of AGU coder and other DCT-based lossy compression techniques.

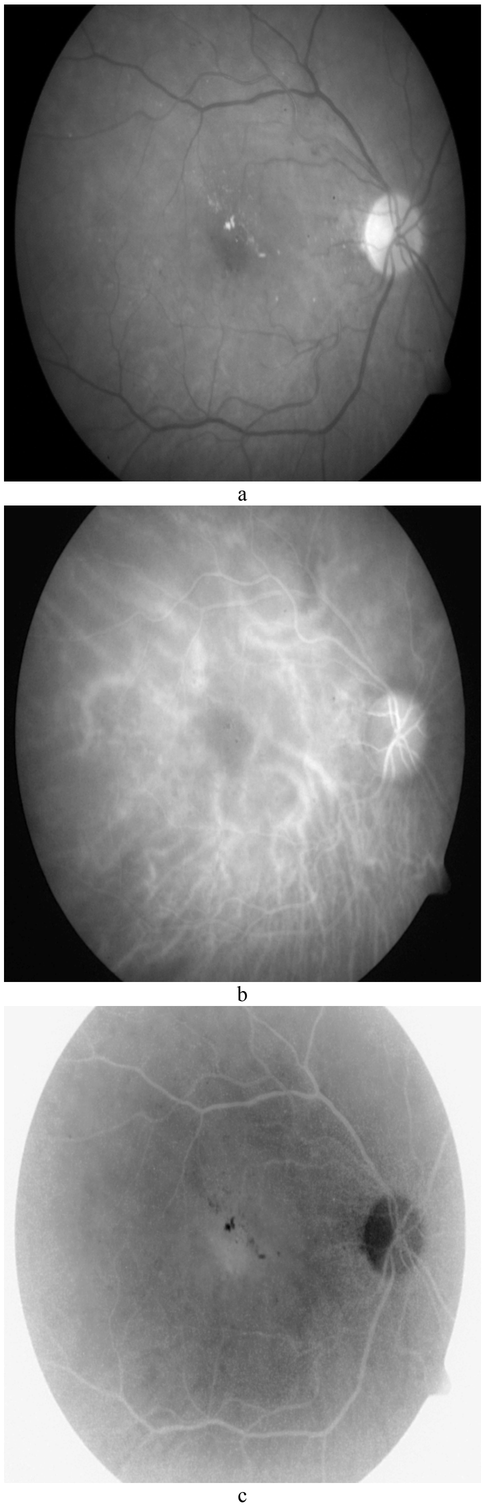


Fig. 8. Y (a), Cr (b) and Cb (c) components of retina color image

a

b

Fig. 9. Original (a) and compressed (b) retina images

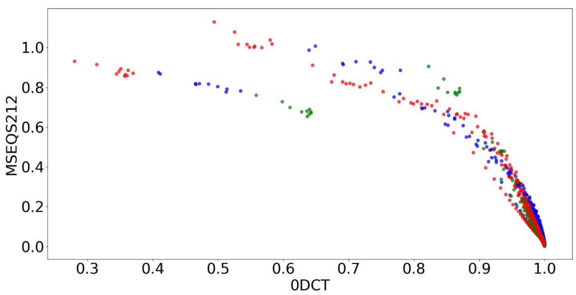


Fig. 10. Scatter-plot of normalized MSE vs P_0 for component-wise compression in YCrCb color system

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